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A Combined Knowledge-Driven and Data-Driven Approach to Selecting Resilient Suppliers Based on Heterogeneous Information (Case Study: Steel Industry)

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Abstract

Intoday's world, competition among firms has evolved into competition among supply chains. Supply chains must be resilient to maintain operational continuity in highly risky, turbulent environments. Suppliers, as the first and outermost layer of the supply chain, are the most vulnerable to risks, and disruptions in supplier performance can affect the entire supply chain. Therefore, incorporating resilience into supplier selection is essential. This study proposes an integrated approach combining Multi-Criteria Decision-Making (MCDM) and machine learning to select resilient suppliers, leveraging both quantitative and qualitative data. First, resilience criteria were identified through a comprehensive literature review, and then localized in collaboration with experts from a domestic steel company. Ultimately, 15 resilience criteria and 17 financial indicators were determined as the final evaluation criteria. To assess suppliers, Shannon entropy and the Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) method were used to weight and calculate resilience scores. These scores, together with financial data, were then used in a machine learning framework comprising Principal Component Analysis (PCA) and K-means clustering. By reducing the data to four principal components, the 24 main suppliers of the case study company were clustered into five groups. Model validity was examined by comparing supplier rankings obtained from the MARCOS and TOPSIS methods, yielding a Spearman correlation coefficient of 0.87, which indicates a strong relationship. In addition, the elbow method and silhouette index confirmed that five clusters were appropriate. By integrating data-driven and knowledge-driven approaches, this research provides a practical step toward improving decision-making in resilient supplier selection.
Keywords: Resilient supplier selection, Heterogeneous information, Knowledge-driven approach, Measurement alternatives and ranking according to compromise solution, Machine learning.

1 | Introduction

With the globalization and expansion of supply chains, the likelihood of exposure to risks and disruptions, and consequently the vulnerability, has increased, highlighting the necessity of addressing supply chain

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resilience [1]. Suppliers are considered the outermost boundary of a supply chain and are exposed to upstream risks and disruptions; therefore, selecting resilient suppliers is recognized as an effective approach to achieving a resilient supply chain [2].

The globalization of activities across industries has transformed sourcing and supplier selection into a global process influenced by political, legal, and cultural factors [3]. Moreover, weaknesses in transportation infrastructure, technology, and production capacity may also affect this process [4]. As supply chain structures become more complex and globalized, manufacturing firms increasingly depend on their suppliers, thereby intensifying their exposure to supply chain risks. Under such conditions, incorporating resilience into supplier selection methodologies becomes essential [5].

In risk management, suppliers represent the most common source of external risks in modern supply chains. Ensuring the continuity of supply chain flows under disruptive events is a critical concern that has drawn firms' attention toward selecting resilient suppliers [6]. Unlike the extensive body of research on traditional and green supplier selection criteria, resilience-related criteria for supplier selection have not yet been sufficiently explored [7]. Supplier selection is a critical responsibility due to its direct impact on the final product and therefore requires continuous attention [4]. This decision also lays the foundation for long-term supplier partnerships, which can contribute to a business's success or failure [8].

Suppliers play a fundamental role in achieving supply chain objectives [9]. To develop a responsive supply chain plan with respect to resilience, the procurement function must place particular emphasis on sourcing decisions. Selecting a resilient supplier is a key strategic decision in supply chain risk management [10]. A resilient supplier typically possesses high adaptability, which helps reduce vulnerability to disruptions, absorb the impacts of adverse events, and recover rapidly from disturbances, thereby ensuring an acceptable level of operational continuity following a disaster [11].

The selection of resilient suppliers is a critical decision for organizational sourcing and for achieving competitive advantage [12]. To date, limited research has addressed resilient supplier selection problems that require the simultaneous consideration of both numerical and linguistic evaluation criteria. These criteria differ fundamentally from those used in traditional supplier selection problems [13]. In logistics 4.0, given the extensive impact of sourcing decisions on supply chain resilience, efficiency, and sustainability, an appropriate decision-making framework is required. The decision-making problem involves evaluating multiple suppliers against conflicting criteria. This problem becomes more complex when decision-related information is heterogeneous, comprising qualitative information that is often imprecise or vague, as well as quantitative information that is difficult to process [14].

Traditional Multi-Criteria Decision-Making (MCDM) approaches are generally unable to effectively address the resilient supplier selection problem in logistics 4.0 due to the large volume of quantitative and qualitative data involved. The emergence of digital technologies such as machine learning, cloud computing, the Internet of Things (IoT), and blockchain has enabled managers and governments to cope with uncertainty through intelligent decision-making principles [5]. The relationship between suppliers and buyers plays a crucial role in the success of modern supply chain management and in achieving strategic objectives. Consequently, the vulnerability of suppliers at the upper tiers of the supply chain has increased with globalization. At the same time, suppliers, as a core component of supply chains, play a vital role in mitigating global risks.

Selecting resilient suppliers is therefore essential for building resilient supply chains. The present study focuses on the resilience dimension of the supplier segment, aiming to achieve a supply chain resilient to disruptions. Due to the heterogeneity of the information and components involved in supplier evaluation, a hybrid, integrated approach combining MCDM tools and machine learning techniques is adopted. Historical data from the firm's information system, along with qualitative data from decision-making experts, are used as input for this research.

This study presents a case study of the Iranian steel industry to examine supplier selection from a resilience perspective. The objective is to evaluate and cluster resilient suppliers using a combination of knowledge-driven and data-driven approaches, based on quantitative and linguistic criteria. The subsequent section reviews the literature on resilient suppliers and identifies the associated research gaps. Section 3 describes the research methodology. Section 4 presents the model implementation and data analysis, and Section 5 provides conclusions and directions for future research.

2 | Literature Review

Parkouhi and Ghadikolaei [4] proposed a model for resilient supplier selection in the wood and paper industry using fuzzy network analysis and the grey VIKOR method. They examined 42 criteria across four dimensions: benefits, opportunities, costs, and risks, and demonstrated that risk is the most critical factor influencing resilience. Suppliers characterized by price diversity, reduced vulnerability, high visibility, and on-time delivery were prioritized. Pramanik et al. [15] developed a quantitative approach for resilient supplier selection by integrating AHP, TOPSIS, and QFD in a fuzzy environment. This approach reduces conflicts among decision-makers and integrates general, technical, and resilience criteria. By employing quality, delivery time, production compliance, buffer capacity criteria, and fuzzy sets, the method enables more accurate judgments, reduces ambiguity, and prevents information loss. Hosseini and Khaled [9] combined the AHP approach with collective classification to identify eight elements related to suppliers' resilience capacity, including absorption, adaptation, and recovery. Using advanced data mining techniques, including binary logistic regression, classification trees, and neural networks, supplier resilience was predicted and subsequently incorporated into a hierarchical analysis to rank the top five suppliers based on general criteria such as quality, cost, responsiveness rate, and lead time. The results indicated that robustness, reliability, and rerouting capability are the most significant resilience factors. Hasan et al. [11] proposed a decision support system–based framework for ranking resilient suppliers in logistics 4.0 using heterogeneous data. This framework employed time-series and triangular fuzzy data to analyze qualitative attributes and ranked suppliers using fuzzy TOPSIS.

Fallahpour et al. [16] introduced a super-hybrid fuzzy framework for selecting sustainable, resilient suppliers in the Malaysian palm oil industry. They identified 30 supplier evaluation criteria across three aspects: general, sustainability, and resilience, and designed a super-hybrid model incorporating FDEMATEL, FBWM, FANP, and FIS for weighting criteria and evaluating supplier performance. The results showed that cost, resource consumption, and agility were the most important sub-criteria, while flexibility, business insurance, and visibility were the least significant. Afrasiabi et al. [17] proposed a hybrid fuzzy MCDM model for selecting sustainable and resilient suppliers. In this approach, the weights of 16 selected criteria across economic, social, environmental, and resilience dimensions were determined using FBWM, and supplier evaluation was conducted using an integrated GRA–TOPSIS method. The results identified pollution control, environmental management systems, and risk awareness as the most important criteria in the sanitary fittings industry. Abedian et al. [18] developed a comprehensive model based on fuzzy set theory and Data Envelopment Analysis (DEA) for selecting green–resilient suppliers in electronic manufacturing systems.

In this model, 12 sub-criteria were considered for supplier evaluation. Fuzzy set theory was used to analyze supplier weights and performance, and to rank them; subsequently, DEA was applied to aggregate data and rank suppliers based on a single dummy input and three output variables. Ulutaş et al. [19] proposed a comprehensive grey MCDM model for resilient supplier selection. In this study, grey PSI (for objective criteria) and grey BWM (for subjective criteria) were used to determine the relative importance of criteria and sub-criteria. Subsequently, grey MCRAT and grey COBRA methods were applied to evaluate and rank suppliers in a textile company. The findings indicate that incorporating resilience attributes into supplier selection can improve risk management and operational resilience, ultimately enhancing competitive advantage and long-term sustainability. Davoudabadi et al. [20] introduced a model combining statistical techniques, decision-making methods, and mathematical programming to evaluate the efficiency of resilient suppliers. In the proposed model, DEA and entropy were employed to determine criterion weights. At the same time, a combination of Principal Component Analysis (PCA) and DEA was used to reduce dimensionality, address criterion correlations, and rank suppliers. One of the key advantages of this approach is the simultaneous utilization of quantitative and subjective data.

Table 1. Literature review categorization.

References	Methodology	Case Study
Pramanik et al. [15]	Fuzzy AHP-TOPSIS-QFD	Computer industry
Parkouhi et al. [21]	Gray DEMATEL-SAW	Wood and paper
Davoudabadi et al. [20]	Entropy-DEA-PCA	Numerical example
Fallahpour et al. [16]	FDEMATEL- FBWM-FANP-FIS	Palm oil
Leong et al. [22]	GRA-BWM-TOPSIS	Food industry
Nasrollahi et al. [23]	DEMATEL-ISM	Desalination supply chain
Nazari-Shirkouhi et al. [24]	ANN-DEA-Z numbers	Pharmacy
Varchandi et al. [25]	BWM-FTOPSIS	e-commerce
Ulutaş et al. [19]	PSI-BWM-MCRAT-COBRA	Textile company
Current study	Entropy-Measurement alternatives and ranking according to compromise solution-PCA-K-means	Steel factory

Considering the gap in the simultaneous use of MCDM approaches and machine learning, in a way that takes advantage of the knowledge and expertise of decision-makers, as well as the identification of hidden patterns in data and their analysis in the selection of resilient suppliers, the present study proposes and presents a combined knowledge-based and data-driven approach to facilitate the process of selecting resilient suppliers in an environment with heterogeneous data and information.

2 | Research Methodology

The present study is a descriptive survey and was conducted at one of the steel manufacturing plants located in Yazd city. In terms of data collection, the research adopts a mixed approach combining library-based and field methods. The most important resilience criteria were extracted from the resilient supplier selection literature and subsequently localized through consultation with experts and industry specialists.

The statistical population consists of managers and experts from the company's purchasing department, and purposive sampling was employed based on individuals' expertise and familiarity with suppliers. The effective criteria were categorized into two groups: qualitative and quantitative. Qualitative (resilience-related) criteria were collected through questionnaires completed by experts, while quantitative (financial) criteria were obtained from the purchasing planning unit.

The weights for the resilience criteria were determined using Shannon entropy, and 24 main suppliers of the company were evaluated using the Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) method. After incorporating suppliers' resilience scores into the financial data, dimensionality reduction was performed using PCA, followed by supplier clustering using the k-means algorithm. Finally, to validate the proposed framework, supplier rankings obtained from the MARCOS method were compared with those from the TOPSIS technique, and the Spearman rank correlation coefficient was calculated. In addition, the elbow method and silhouette index were employed to determine the optimal number of clusters. The main steps of the proposed model are described below.

The weights for the resilience criteria are calculated using Shannon entropy to reduce the influence of subjective judgments and enhance objectivity. This method is data-driven and widely applied in decision-making problems. The procedure consists of three main steps: normalization of the decision matrix, calculation of the entropy value for each criterion, and determination of the corresponding weights. Criteria with lower entropy values receive higher weights, as they provide more useful information. It should be noted that the computation of weights differs depending on whether the criteria are benefit- or cost-type [26].

After determining the resilience criteria weights using the Shannon entropy method, supplier performance is evaluated using the MARCOS technique. This method, introduced by Stević et al. [27] in 2020, identifies the best alternative by defining two reference solutions (ideal and anti-ideal) and calculating the relative position of each alternative with respect to these solutions. In this approach, ranking is performed based on the final utility function values, and the alternative with the highest value is considered the best supplier [28]. The steps of the MARCOS method are as follows.

Step 1. Using *Eqs. (2)* and *(3)*, the initial decision matrix is extended and standardized by adding the anti-ideal and ideal solutions, where B denotes the set of benefit criteria. C represents the set of cost criteria.

$$X = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \cdots \\ A_m \\ AI \end{array} \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix}. \quad (1)$$

$$AAI = \min_i x_{ij}. j\epsilon B, \quad \max_i x_{ij}. j\epsilon C. \quad (2)$$

$$AI = \max_i x_{ij}. j\epsilon B, \quad \min_i x_{ij}. j\epsilon C. \quad (3)$$

Step 2. The expanded initial decision matrix (X) is normalized. The elements of the normalized matrix N= $[n_{ij}]$ (m×n) are obtained using *Relations (4)* and *(5)*.

$$n_{ij} = \frac{x_{ai}}{x_{ij}}. j\epsilon C. \quad (4)$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}}. j\epsilon B. \quad (5)$$

Step 3. The weighted matrix V= $[v_{ij}]$ (m×n) is formed from the product of the normalized matrix N and the weight coefficients of each criterion (obtained from the Shannon entropy method), according to *Eq. (6)*.

$$v_{ij} = n_{ij} \times w_j. \quad (6)$$

Step 4. The degree of desirability of the K_i alternative relative to the anti-ideal and ideal solutions is estimated using *Relations (7)* and *(8)*, where Si (i=1, 2… m) represents the sum of the elements of the weighted matrix V.

$$K_i^- = \frac{S_i}{S_{aai}}. \quad (7)$$

$$K_i^+ = \frac{S_i}{S_{ai}}. \quad (8)$$

Step 5. The utility function of the options, the compromise of the observed option in relation to the ideal and anti-ideal solutions, is determined using *Eq. (9)*.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}}. \quad (9)$$

The utility functions for the ideal and anti-ideal solutions are obtained by applying *Relations (10)* and *(11)*.

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}. \quad (10)$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}. \quad (11)$$

Step 6. The alternatives (suppliers) are ranked according to the final values of their utility functions. A higher value indicates a more desirable alternative [27], [28].

Prioritizing suppliers based on qualitative supplier selection criteria is challenging because it requires human judgment. Such evaluations may appear vague and are often difficult to interpret [29]. Due to decision-makers' sometimes ambiguous or inadequate knowledge, machine learning approaches are employed to complement and support the decision-making process. By integrating knowledge-based and data-driven approaches, the advantages of both can be simultaneously exploited. In this study, the output of the supplier evaluation technique (the MARCOS method) enables qualitative criteria to be measured and quantified. Consequently, a column titled supplier score can be readily added to the financial data, which is inherently quantitative.

Subsequently, PCA is applied to reduce the dimensionality of the data in the supplier selection process. This method facilitates decision-making by eliminating indicator correlations and identifying hidden patterns in complex datasets. Principal components are obtained as linear combinations of the original variables, and the first principal component accounts for the maximum variance in the data [13]. This approach transforms complex data into a smaller set of principal components that are more suitable for subsequent analyses.

Step 1. The decision matrix is constructed according to *Eq. (12)*, where n denotes the number of suppliers and p represents the number of criteria

$$L = (X_1.X_2.\dots.X_P) = \begin{bmatrix} X_{11}.X_{12}.\dots.X_{1P} \\ X_{21}.X_{22}.\dots.X_{2P} \\ \dots \\ \dots \\ \dots \\ X_{n1}.X_{n2}.\dots.X_{nP} \end{bmatrix}. \quad (12)$$

Step 2. Data normalization is performed using *Relations (13)* and *(14)* for the input and output data, respectively.

$$L' = \frac{L_i}{\max L_i}. \quad (13)$$

$$L' = \frac{\min L_i}{L_i}. \quad (14)$$

Since L' is a scale-free (dimensionless) data, a different normalization procedure must be used for the inputs and outputs, as provided by L'; then, the matrix L' is used as input to continue the PCA process *Eq. (15).*

$$L' = \left(X'_1.X'_2.\dots.X'_p\right) = \begin{bmatrix} X'_{11}.X'_{12}.\dots.X'_{1P} \\ X'_{21}.X'_{22}.\dots.X'_{2P} \\ \dots \\ \dots \\ \dots \\ X'_{n1}.X'_{n2}.\dots.X'_{nP} \end{bmatrix}. \quad (15)$$

Step 3. The covariance matrix V is obtained using *Eq. (16).*

$$V_{ik} = \frac{1}{n}\sum_{j=1}^{n}\left(X'_{ji} - \overline{X}'_i\right)\left(X'_{jk} - \overline{X}'_k\right).i = 1.2.\dots.p.k = 1.2.\dots.p. \quad (16)$$

Step 4. The eigenvalues and eigenvectors of the covariance matrix are obtained from *Eq. (17).* λ is a set of eigenvalues.

$$|V - \lambda I| = 0, VX' = \lambda X'. \quad (17)$$

Step 5. The normalized eigenvalues are equivalent to the principal components. The maximum eigenvalue refers to the first vector and represents the first principal component. Consider the eigenvalues according to *Eq. (18)* and the corresponding normalized eigenvectors α_1, α_2, and α_p.

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_P \geq 0. \quad (18)$$

$$\begin{bmatrix} X_{PC_1} \\ X_{PC_2} \\ \cdot \\ \cdot \\ \cdot \\ X_{PC_P} \end{bmatrix}_{P\times 1} = \begin{bmatrix} \alpha_{11}.\alpha_{12}.\dots.\alpha_{1P} \\ \alpha_{21}.\alpha_{22}.\dots.\alpha_{2P} \\ \dots \\ \dots \\ \dots \\ \alpha_{P1}.\alpha_{P2}.\dots.\alpha_{PP} \end{bmatrix}_{P\times P} \times \begin{bmatrix} X'_1 \\ X'_2 \\ \cdot \\ \cdot \\ \cdot \\ X'_P \end{bmatrix}_{P\times 1}. \tag{19}$$

According to *Eq. (19)*, X_{pci} (i=1, 2… p) is the $i-th$ principal component and is the linear combination of X_1', X_2'… X_p' (i.e., the original normalized variables). It should be noted that each principal component is formed as a linear combination of the original data set by *Eq. (20)*. *Eqs. (21)* and *(22)* are used to calculate the variance and covariance matrices of the variables [30].

$$X_{PC_i} = \alpha_{i1}X_1' + \alpha_{i2}X_2' + \dots + \alpha_{iP}X_P'.\, i = 1.2.\dots.p. \tag{20}$$

$$\mathrm{Var}(X_{PC_i}) = \alpha_i^t V \alpha_i.\, i = 1.2.\dots.p. \tag{21}$$

$$\mathrm{Cov}(X_{PC_i}.X_{PC_k}) = \alpha_i^t V \alpha_k.\, i = 1.2.\dots.p.\, k = 1.2.\dots.p. \tag{22}$$

In the final stage of the proposed framework, namely supplier clustering, the k-means algorithm was employed. This algorithm is an unsupervised learning technique that partitions and groups objects based on their characteristics. The clustering process is performed by minimizing the sum of squared distances between data points and their corresponding cluster centers. The k-means algorithm partitions a dataset containing n objects or records into k clusters (k < n), so that intra-cluster similarity is maximized and inter-cluster similarity is minimized. In other words, clustering groups data objects so that the within-cluster distances are small and the between-cluster distances are large. The similarity within each cluster is measured with respect to the mean (average) of the objects in that cluster, called the cluster center.

The inputs of this algorithm include n, the number of objects in the dataset; k, the number of clusters; and d, the number of data dimensions. The output is a set of k clusters that minimizes the mean squared error criterion. The main steps of the algorithm include determining the number of clusters, selecting initial cluster centers, calculating distances between data points and their centers, grouping data points, and recalculating the cluster centers until convergence. Finally, the quality of the clusters is evaluated using the mean squared error criterion in *Eq. (23)*, and the algorithm continues until changes in the clusters cease (convergence) [31], [32].

$$\mathrm{MSE} = \frac{1}{n}\sum\sum(p - m_i)^2. \tag{23}$$

To assess the validity of the proposed approach, two methods were employed. First, the rankings of suppliers obtained using the TOPSIS and MARCOS techniques were compared, and the correlation between the rankings was calculated using the Spearman correlation coefficient. Second, the elbow method and silhouette index were used to determine the optimal number of clusters for the clustering algorithm.

The TOPSIS method benefits from simple computational procedures and the ability to provide a logical representation of performance, enabling the comparison and ranking of alternatives based on multiple criteria. In this method, alternatives are ranked according to their distances from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). Initially, the original decision matrix is normalized and then weighted. Subsequently, the positive and NISs are determined based on the nature of the criteria (benefit or cost). In the next step, the distance of each alternative from the PIS and NIS is calculated. Finally, the closeness coefficient of each alternative to the PIS is computed, and the alternatives are ranked based on these coefficients [22]. After calculating supplier rankings using the TOPSIS method, they are compared with those obtained using the MARCOS method. The degree of agreement between the rankings is measured using the Spearman rank correlation coefficient (24). A value of ϱ close to 1 indicates a high level of agreement between the two methods, whereas a value close to 0 indicates no agreement, and a value close to −1 implies a reverse ranking [33].

$$\rho = 1 - \frac{6\sum d_2^i}{n(n^2-1)}. \quad (24)$$

To determine the appropriate number of clusters in the k-means algorithm, the elbow method and the silhouette index are employed. The elbow method minimizes the Within-Cluster Sum of Squares (WCSS) and illustrates the gradual change in WCSS through an "elbow" plot. The point at which the reduction in WCSS begins to slow down indicates the optimal number of clusters [34]. The silhouette index *Eq. (25)* also analyzes the distances between clusters and identifies how effectively data points are assigned within their respective clusters [32]. These two methods are used in complementary ways to determine the optimal number of clusters in supplier clustering.

$$S_j = \frac{p(j) - q(j)}{\max\,(p(j).\,q(j))}. \quad (25)$$

4 | Results

To implement the proposed research model, a steel industry company was selected as a case study. First, scientific articles on resilience were reviewed, and resilience criteria for selecting resilient suppliers were extracted and shared with the company's experts. They selected and introduced 15 practical resilience indicators (*Table 2*).

Table 2. Finalized resilience criteria and their descriptions.

Symbol	Resilience Indicator	Description
RC1	Capacity increase ability	The ability to adjust product volume in response to the buyer's request.
RC2	Information sharing	The willingness of vendors/suppliers to share relevant information with their customers.
RC3	Flexibility	Readiness to react to various supply chain turbulences.
RC4	Continuity and cooperation	The willingness of vendors/suppliers to continue cooperation with customers to develop proactive and reactive plans for a resilient business.
RC5	Cost control ability	The supplier's ability to control the total supply chain costs it provides.
RC6	Reorganization	The ability to quickly integrate resources and rebuild organizational culture and structure.
RC7	Agility	The supplier's ability to produce the product quickly.
RC8	Reputation and brand	The supplier's reputation and stakeholder opinions, quantitatively.
RC9	Reliability	The supplier's ability to consistently deliver acceptable raw materials or products on time.
RC10	Product customization	A corrective method for incorporating any engineering design changes into the product; suppliers must have engineering capabilities to respond to changes in customer taste or needs.
RC11	Safety stock	The supplier's capacity to maintain sufficient quantities of essential materials and goods to support customers during a disruptive event.
RC12	On-time delivery	The ability to follow a predefined delivery schedule.

Table 2. Continued.

Symbol	Resilience Indicator	Description
RC13	Quality of products and services	The ability of the provided goods to meet customer expectations.
RC14	Responsiveness speed	The speed of the supplier's response to market demand.
RC15	Robustness	Physical protection infrastructure and safety systems for the supplier's buildings and facilities to minimize the negative impacts of disruptions, especially during natural disasters.

In addition to resilience indicators, which overlap with conventional supplier selection criteria, financial indicators were also important in the organization under study's supplier evaluation process. Due to limited access to appropriate quantitative resilience data, financial data was used as a proxy. The 17 financial indicators provided by this company are listed in *Table 3*.

Table 3. Financial indicators and their descriptions.

Symbol	Financial Indicator	Description
FC1	Gross profit margin	Cost of goods sold is subtracted from revenue and divided by revenue.
FC2	Operating profit margin	Calculated as operating income before depreciation divided by sales.
FC3	Pre-tax profit margin	Measures the remaining profit when all operating and non-operating expenses, except taxes, are deducted.
FC4	Net profit	Represents the final result of the company's activity, estimated by subtracting all expenses, including income tax, from revenue.
FC5	Return on Assets (ROA)	Net profit divided by total assets.
FC6	Return on Equity (ROE)	Net profit divided by shareholders' equity.
FC7	Asset turnover	Measures the company's ability to generate revenue from its assets.
FC8	Fixed assets	Describes the availability of the company's current assets compared to total current liabilities.
FC9	Inventory turnover	Refers to the increase in inventory resulting from increased activity or a change in inventory policy.
FC10	Accounts receivable turnover	Ratio of sales revenue to average sales.
FC11	Debt ratio	Total liabilities divided by total assets.
FC12	Debt to equity ratio	Indicates the company's ability to fulfill all its obligations, determined by the ratio of share capital used to pay debt.
FC13	Interest coverage ratio	Indicates the ratio of net operating income to interest expense.

Table 3. Continued.

Symbol	Financial Indicator	Description
FC14	Current ratio	Calculated as current assets divided by total short-term liabilities.
FC15	Quick ratio	Inventory is subtracted from current assets and divided by short-term liabilities.
FC16	Cash ratio	Calculated as the amount of cash divided by short-term liabilities.
FC17	P/E ratio	Ratio of market value per share to earnings per share.

In the proposed supplier evaluation approach, the required information was collected through collaboration with the following: financial data for 24 main suppliers and 17 associated financial indicators. In addition, 15 criteria influencing supplier resilience were extracted from the existing literature, and after localization, experts were asked to evaluate suppliers based on these criteria using a Likert-scale questionnaire.

After data collection, the initial decision matrices were quantified according to the benefit or cost nature of the criteria. To aggregate the experts' judgments, the geometric mean method was used, and the results were presented as an integrated, quantified decision matrix.

To determine the weights of the selected resilience indicators, the Shannon entropy technique was applied. In this process, the integrated quantified decision matrix was first normalized, and then the entropy value of each indicator was calculated. Subsequently, the degree of divergence for each indicator was determined, and its normalized weights were obtained. The resulting values are presented in Table 4, which illustrates the weight of each indicator.

Based on these results, the resilience indicator weights were used to calculate the suppliers' scores and rankings in the next step. Among these indicators, the criteria of product and service quality, reliability, agility, responsiveness, and on-time delivery were found to be the most important, respectively, compared with the other criteria.

Table 4. Entropy, degree of deviation, and final weight of each indicator.

Symbol	Entropy	Degree of Deviation	Final Weight	Rank
RC1	0.974	0.026	0.0484	14
RC2	0.9672	0.0328	0.0609	11
RC3	0.9645	0.0355	0.0659	9
RC4	0.9635	0.0365	0.0679	7
RC5	0.9671	0.0329	0.0612	10
RC6	0.9723	0.0277	0.0515	12
RC7	0.9573	0.0427	0.0794	3
RC8	0.9623	0.0377	0.0701	6
RC9	0.9518	0.0482	0.0896	2
RC10	0.9642	0.0358	0.0665	8
RC11	0.979	0.021	0.039	15
RC12	0.9618	0.0382	0.071	5
RC13	0.9431	0.0569	0.1057	1
RC14	0.9607	0.0393	0.0731	4
RC15	0.9732	0.0268	0.0499	13

Subsequently, the novel MARCOS technique was employed to evaluate the performance and rank the suppliers. The first step of the MARCOS method is to construct the extended initial decision matrix. As previously stated, after quantifying the decision matrices, the decision-makers' evaluations were aggregated using the geometric mean. The extended initial decision matrix was then formed by adding two rows, namely AAI and AI, which represent the anti-ideal solution and the ideal solution, respectively, to the aggregated quantitative decision matrix.

In this study, all resilience criteria are of a benefit-type nature. Therefore, the AAI (anti-ideal solution) and AI (ideal solution) rows reflect the minimum and maximum values, respectively (based on *Eqs. (2)* and *(3)*). In the next step, the extended initial decision matrix is normalized. Depending on the criterion type (cost or benefit), either a maximization or a minimization function is applied. Given the benefit-type nature of the criteria, a simple linear normalization was used.

Subsequently, the weighted normalized matrix was obtained by multiplying the importance weights of each criterion, derived from the Shannon entropy technique, by the elements of the normalized matrix. The sum of the elements in each row of the weighted normalized matrix was then calculated, followed by the computation of the degrees of desirability. Afterward, the utility functions corresponding to the ideal and anti-ideal solutions were determined. Finally, the suppliers' scores were obtained by calculating the final utility function based on *Eq. (9)*, and their rankings were determined accordingly. The results of the MARCOS method are presented in *Table 5*.

According to the results, supplier S24 achieved a score of 0.73 and ranked first among the 24 suppliers. Subsequently, suppliers S23, S18, S10, and S1 ranked second to fifth with scores of 0.65, 0.62, 0.59, and 0.58, respectively. In addition, supplier S17, with a score of 0.27, ranked last. Suppliers S13 and S21 simultaneously obtained the 22nd rank.

To integrate heterogeneous information, the proposed framework creates a unified dataset by adding suppliers' resilience scores (calculated using the MARCOS method based on expert judgments) to the financial data, thereby combining data-driven and knowledge-driven information. This dataset consists of 18 indicators (17 financial indicators and one indicator, the supplier score, representing supplier resilience). It uses data from 24 suppliers of the case study company for machine learning analyses and resilient supplier selection.

Before implementing the PCA method, five assumptions must be examined to ensure the validity of the results. These assumptions include: measurement of variables at a continuous level, the existence of linear relationships among variables, sampling adequacy, sufficient correlation among variables, and the absence of significant outliers. After verifying these assumptions and confirming that none were violated, the PCA was applied to the dataset using SPSS. Subsequently, the results and outputs obtained from the PCA model were interpreted.

Table 5. Results of the MARCOS technique.

Supplier	Ki-	Ki+	f(Ki-)	f(Ki+)	Score	Rank
S1	2.94	0.604	0.17	0.83	0.58356	5
S2	2.49	0.511	0.17	0.83	0.493841	16
S23	3.3	0.679	0.17	0.83	0.655679	2
S24	3.69	0.758	0.17	0.83	0.732062	1

Table 6 presents the initial and extracted communalities of each variable with respect to the extracted components. The Initial values represent the initial communalities (before extraction) and indicate the total variance of each variable that the components can explain. Therefore, this value is initially equal to 1 for all variables. The Extraction column reports the communalities after principal component extraction. The closer these values are to 1, the better the extracted components explain the original variables.

The results indicate that all variables in the dataset of this study are suitable for explaining variance after factor extraction. The lowest communality value is for variable FC16; however, since it exceeds the 0.5 threshold, there is no need to remove this variable or re-estimate the model.

Table 6. Communalities.

	Initial	Extraction
FC1	1.000	0.939
FC2	1.000	0.882
FC3	1.000	0.963
FC4	1.000	0.951
FC5	1.000	0.929
FC6	1.000	0.815
FC7	1.000	0.943
FC8	1.000	0.862
FC9	1.000	0.738
FC10	1.000	0.789
FC11	1.000	0.697
FC12	1.000	0.859
FC13	1.000	0.669
FC14	1.000	0.753
FC15	1.000	0.795
FC16	1.000	0.511
FC17	1.000	0.655
Score	1.000	0.899

In the total variance explained table (*Table 7*), initially, several components equal to the number of variables in the original dataset (18 criteria) are extracted. The initial eigenvalues for each component are reported in the second column. Components with eigenvalues greater than one represent genuine principal components. According to this table, of the 18 variables, four principal components have eigenvalues greater than 1. These components account for 31.65%, 24.43%, 15.69%, and 9.60% of the total variance, respectively, which together explain 81.37% of the total variance.

Table 7. Total variance explained.

Total Variance Explained									
Initial Eigenvalues				Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.497	41.648	41.648	7.497	41.648	41.648	5.698	31.655	31.655
2	3.752	20.844	62.491	3.752	20.844	62.491	4.397	24.427	56.082
3	2.085	11.581	74.072	2.085	11.581	74.072	2.824	15.691	71.773
4	1.314	7.299	81.371	1.314	7.299	81.371	1.728	9.598	81.371
5	0.904	5.022	86.393						
6	0.645	3.584	89.977						
7	581	3.231	93.208						
8	444	2.465	95.673						
9	261	1.450	97.123						
10	0.140	0.780	97.903						
11	117	0.648	98.551						
12	0.084	0.467	99.017						
13	0.066	366	99.383						
14	0.041	230	99.614						
15	0.025	0.141	99.755						
16	0.021	0.115	99.870						
17	013	075	99.945						
18	010	055	100.000						
Extraction method: PCA.									

The scree plot (*Fig. 1*) confirms the findings obtained from the total variance explained table (*Table 7*). As shown in the figure, only the eigenvalues of the four components lie above the red line (greater than one). The sharp decline between the first and fourth components indicates the importance of these four components in explaining the total variance of the data. In contrast, the remaining components show no significant decrease in eigenvalues, suggesting they cannot adequately represent the overall data variability.

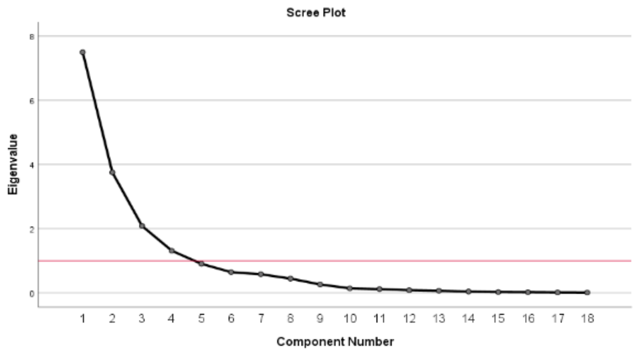

Fig. 1. Scree chart.

Table 8 presents the unrotated component (factor) matrix, which indicates the degree of correlation between each variable and the extracted components (with eigenvalues greater than one). The rotated component matrix (*Table 9*) shows the correlations between the rotated components and the observed variables. In the first component, variable FC3, with a correlation of 0.916, was identified as the most influential. Similarly, in the second, third, and fourth components, variables FC7, FC17, and FC12 exhibited the highest correlations and impacts, with values of 0.905, 0.773, and 0.885, respectively. It should be noted that in this table, only factor loadings greater than 0.5 are reported.

Table 8. Component matrices.

	Component			
	1	2	3	4
FC5	0.916			
score	0.898			
FC3	0.852			
FC4	0.842			
FC14	0.779			
FC11	-0.763			
FC15	0.743			
FC2	0.724			
FC8	0.653	0.559		
FC6	0.649		-0.502	
FC13	0.635		-0.507	
FC16	0.514			
FC7		0.826		
FC1	0.514	-0.771		
FC9		0.756		
FC10		0.718		
FC17			0.791	
FC12				0.786

Table 9. Rotated component matrices.

	Component			
	1	2	3	4
FC3	0.950			
FC4	0.940			
FC2	0.928			
FC1	0.868			
FC5	0.708	0.593		

Table 9. Continued.

	Component			
	1	2	3	4
FC13	0.611			
FC7		0.905		
FC8		0.897		
FC6		0.768		
FC11	-0.501	-0.615		
FC9		0.589		
FC17			0.773	
FC15			0.680	
FC14			0.620	
score	0.564		0.609	
FC16			0.569	
FC12				0.885
FC10				0.707

The component transformation matrix (*Table 10*) shows the degree of correlation between the four extracted components before and after the cycle.

Table 10. Component transformation matrix.

Component	1	2	3	4
1	0.754	0.543	0.367	0.041
2	-0.590	0.682	0.160	0.402
3	-0.148	-0.407	0.894	0.115
4	0.246	-0.274	-0.201	0.908

Extraction method: PCA.
rotation method: varimax with Kaiser normalization.

After applying PCA to identify latent patterns and reduce data dimensionality, the k-means clustering method was employed to group suppliers into core, backup, and alternative suppliers. To determine the appropriate number of clusters, k was varied from 2 to 8, and the corresponding outputs were collected. The results indicated that the changes in the total within-cluster distances for k values between 2 and 5 were significantly greater than those observed for k values between 5 and 8 (*Table 11*). Therefore, k = 5 was examined in greater detail. Optimal k-means clustering is achieved when the variability resulting from changes in the number of clusters (k) is minimized.

Table 11. Sum of distances between clusters for k between 2 and 8.

8	7	6	5	4	3	2	**Cluster**
19.70	21.48	24.01	25.51	30.91	36.78	41.44	**Score**

Table 12 shows the initial centers of these five clusters in four dimensions (due to the presence of four variables).

Table 12. Initial cluster centers.

	Cluster				
	1	2	3	4	5
REGR factor score 1 for analysis 1	1.68789	0.49971	-0.47475	-1.11208	-1.23979
REGR factor score 2 for analysis 1	-0.62075	-1.25531	0.79039	-.17371	-1.31847
REGR factor score 3 for analysis 1	-0.69694	2.73581	1.59161	-1.50154	-1.13995
REGR factor score 4 for analysis 1	-0.37218	-0.86532	0.73759	-1.31411	1.69419

The algorithm is repeated until the final cluster centers are reached (convergence). In the last iteration of the algorithm, the cluster centers are shown in *Table 13*.

Table 13. Final cluster centers.

	Cluster				
	1	2	3	4	5
REGR factor score 1 for analysis 1	1.07638	0.49971	-0.39427	-1.47256	-0.38474
REGR factor score 2 for analysis 1	-0.04369	-1.25531	1.00019	-0.81763	-0.98594
REGR factor score 3 for analysis 1	-0.36658	2.73581	0.53514	-0.87823	-0.36239
REGR factor score 4 for analysis 1	-0.28952	-0.86532	0.15636	-1.31171	1.46645

The distances between the centers of the final clusters in the last iteration are as shown in *Table 14*.

Table 14. Distances between final cluster centers.

Cluster	1	2	3	4	5
1		3.429	2.065	2.899	2.471
2	3.429		3.431	4.164	3.986
3	2.065	3.431		2.936	2.543
4	2.899	4.164	2.936		3.032
5	2.471	3.986	2.543	3.032	

In the Analysis Of Variance (ANOVA) test, by examining the significance level (sig.) of the variables, the results in *Table 15* show that for all variables, the sig. value is less than 0.001. Therefore, the assumption of cluster homogeneity is rejected, and the five clusters are significantly different from one another. The F tests should be used only for descriptive purposes, as the clusters have been chosen to maximize differences among cases within clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Table 15. ANOVA results.

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
REGR factor score 1 for analysis 1	4.465	4	0.271	19	16.503	0.000
REGR factor score 2 for analysis 1	3.872	4	0.395	19	9.793	0.000
REGR factor score 3 for analysis 1	3.422	4	0.490	19	6.985	0.001
REGR factor score 4 for analysis 1	3.845	4	0.401	19	9.585	0.000

Table 16 shows the number of suppliers belonging to the five designated clusters. Cluster 1 has eight suppliers, and clusters 2 to 5 have one, eight, three, and four suppliers, respectively. *Table 17* also shows the cluster number of each supplier.

Table 16. Number of cases in each cluster.

Cluster	1	8.000
	2	1.000
	3	8.000
	4	3.000
	5	4.000
Valid		24.000
Missing		.000

Table 17. Cluster numbers for 24 suppliers.

Supplier	Cluster Number	Supplier	Cluster Number	Supplier	Cluster Number	Supplier	Cluster Number
S1	1	S7	5	S13	4	S19	5
S2	1	S8	3	S14	33	S20	1
S3	3	S9	1	S15	4	S21	5
S4	1	S10	3	S16	3	S22	3
S5	5	S11	1	S17	4	S23	3
S6	1	S12	1	S18	3	S24	2

To validate a portion of the proposed framework, the supplier rankings from the Marcus and TOPSIS methods were compared, and the Spearman correlation coefficient was calculated. *Table 18* shows the scores and rankings of suppliers in the TOPSIS technique. The correlation coefficient between the supplier rankings obtained using the mentioned method was 0.87, indicating a strong relationship between the results of these two MCDM techniques.

Table 18. Score and rank of each supplier using the TOPSIS method.

Supplier	Score	Rank	Supplier	Score	Rank
S1	0.4078	11	S13	0.1755	22
S2	0.4084	10	S14	0.4983	3
S3	0.4201	8	S15	0.1881	21
S4	0.3785	14	S16	0.3798	13
S5	0.286	19	S17	0.098	24
S6	0.3321	17	S18	0.4177	9
S7	0.2577	20	S19	0.3278	18
S8	0.4717	4	S20	0.3616	16
S9	0.4534	6	S21	0.1511	23
S10	0.4704	5	S22	0.4328	7
S11	0.3679	15	S23	0.5675	2
S12	0.4044	12	S24	0.6347	1

Also, an elbow diagram was drawn to determine the appropriate number of clusters for values between 2 and 10. The diagram in *Fig. 2* indicates that 5 clusters are the optimal number.

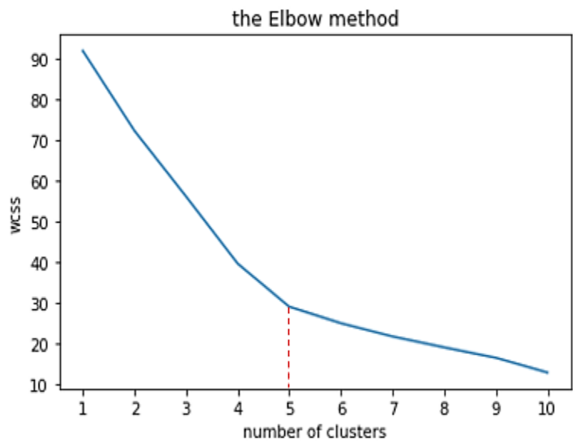

Fig. 2. Elbow diagram and its breakpoint (appropriate number of clusters=5).

The profile index output for the number of clusters between 2 and 6 showed that the number of clusters was 5 (*Table 19*). Although none of the cluster numbers approached 1, this result is still acceptable and consistent with the elbow diagram. Due to the nature of the data and the proximity of the clusters, the profile index value is not close to one. Finally, the appropriate number of clusters for the supplier's dataset would be five.

Table 19. Profile index for 2 to 6 clusters.

Average	Cluster
0.2734	2
0.2297	3
0.2928	4
0.3247	5
0.2903	6

5 | Conclusion

This study evaluated suppliers' resilience under critical conditions and proposed a systematic framework to facilitate decision-making. Using MCDM techniques such as Shannon entropy and MARCOS, the resilience of suppliers was assessed. Then, the suppliers' resilience scores were combined with financial data, reduced in dimensionality using PCA, and the suppliers were subsequently clustered using the k-means algorithm. Ultimately, 24 suppliers were allocated into five clusters. The model's results were validated by comparing the MARCOS and TOPSIS methods and by calculating the Spearman correlation coefficient (0.87). By leveraging the strengths of both data-driven and knowledge-driven methods, this framework can serve as an integrated decision-support system for supplier evaluation and other strategic organizational decisions. It is recommended that future research consider environmental and sustainability factors in supplier selection, the use of big data, and the application of the model in sensitive industries requiring high resilience.

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Data Availability

All data are included in the text.

Conflict of Interest

The authors declare no conflict of interest.

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